A spatial analysis of the abundance and proximity of greenspaces on mental health and house prices across the London boroughs.

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**Introduction**

Humans have always been one with nature, perhaps linking back to our evolutionary past as tree-dwelling beings who were fully emersed in the natural environment. Since then, evolution has brought us to a stage in history where population growth and an influx of mass urbanisation means ‘concrete jungles’ are our new dwellings and high-rise apartment buildings serve as a new abode in place of where trees used to house the masses. Even so, people still feel the need to keep nature close, and pockets of green are still dotted around everywhere we go in the form of greenspaces and parks, even the most recognisable ‘concrete jungle’ of them all, New York City, is home to the world’s most famous greenspace, the 840 acres that is Central Park (Rosenzweig & Blackmar 1991). London is no different, if anything it is actually a world-leader in greenspace allotment, with London.gov.uk (2019) declaring there are over 3,000 parks and greenspaces across the city and Sadiq Khan, the mayor of London recently launching a ‘green city’ strategy that includes London reaching 50% greenspace coverage by 2050 (Edwards 2017). Greenspaces refer to a wider range of areas than parks, they include any areas of vegetation that have been allocated for a recreational, aesthetical or environmental purpose (Houlden et al. 2019) and have almost become a necessity across urban areas. Whilst it is not possible or practical to enforce any laws regarding people’s proximity to greenspaces, the UK government and the EU provide a recommendation that people should live no less than 300m (about 5 minutes’ walk) from a greenspace (Natural England 2010). This close proximity of a greenspace would promote exercise, reduce stress, present an area for children to play and also in today’s ‘pandemic-filled’ world these greenspaces are increasingly important as not only are they a possible ‘escape’ from the confinements of a house that is caught in a pandemic-lockdown, but also, they present an excellent location outdoors to meet up with people for walks or conversations, to get out of your house safely whilst keeping in line with governmental guidelines (Pouso et al. 2021).

As mentioned mass population growth is occurring worldwide leading to more compact and dense cities that are increasingly adding to rising pollution levels (Russo & Cirella 2018). Greenspaces are a key attribute towards combatting this pollution globally (Zupancic et al. 2015). Strategies like Sadiq Khan’s involve making use of all possible parts of cities to increase greenery: garden rooftops (Taylor & Hochuli 2017), green walls (Chen et al. 2020) and repurposed disused train tracks (Wysmulek et al. 2020) to name a few commonly used urban spaces for greenery. For a sustained continual growth of the population it is of ever-growing importance that we try to maintain pollution levels in order to try regain some control over CO2 levels in the atmosphere (de Sherbinin et al. 2007), therefore these evermore inventive urban greenspaces making use of areas which in the past may have been totally disregarded as possible greenery locations, certainly provide aid towards reaching this goal.

Research suggests that proximity to greenspaces may reduce mental health issues (Houlden et al. 2019, Gascon et al. 2015, Pouso et al. 2021), delay mortality rates, and provide general increase in well-being for those in close contact with it (James et al 2015). This project will look at the frequency of greenspaces across the boroughs of London whilst also looking at various socio-demographic sectors within the boroughs themselves to determine any trends or correlations. The project will aim to determine the effect greenspaces have on mental health statistics within London boroughs and try to determine if in fact these areas do cause stress relief (Ulrich et al 1991) and ultimately lower levels of mental health issues. Housing prices will also be examined across the study area in order to determine if the location of greenspaces presents any effect on the economic value of houses. It has been proposed that due to the positive effects of greenspaces including recreation facilities, reduction of air pollution and introduction of natural aesthetics (Carmargo 2016), that an abundance of greenspaces should therefore potentially increase house prices, this hypothesis will be tested in this project also.

**Methods**

The data used in this work came from multiple sources. The location of greenspaces was supplied by Ordnance Survey (OS) mapping, completed on behalf of the greenspace Information for Greater London CIC (GiGL, 2020). This is a collection of information and boundary locations collected from the mid 1980s to 2008, which is available on the GiGL Open Space database and also supplied through the open data portal data.gov.uk. The mental health data used was supplied by the North East Physician Hospital Organisation (NEPHO), who collected the data for the assessment of common mental health problems across the boroughs of London, which was able to be linked to the greenspaces data. The data originally assessed numerous mental health issues ranging from prevalence of phobias, to rates of depressive episodes. The data was cleaned and adapted to more suit this study, some of the less fitting variables were removed; e.g phobias were not seen as a fitting factor to use for comparison of greenspaces to mental health issues and so were dropped from the dataset. It was also decided to only use the rates per 1000 in order to give a more general overview of mental health rates across the boroughs.

House price data in London was also supplied, this provided data points across all of London with characteristics of the house: price, number of rooms, year, house type. This data provides a key metric to measure more/less expensive areas around London which can be correlated towards the location of greenspaces and possibly attributed to the mental health data also.

The study space itself is the boroughs of Greater London, of which there are 33 spread out across 1,572km2 (Moulery et al 2020). This study area provides a huge selection of variability, covering the whole area of one of the top 5 most diverse cities in the world (WCCF, 2015). The data used for analysis provides a broad range of socio-demographics that provide a surplus of information with which it is possible to fully uncover the diversity present in London along with the correlations and influences of the variables looked at. London itself has the river Thames running right through the middle of it East to West, it provides a borough to borough boundary for almost its whole journey through London, but actually goes right through Richmond-Upon-Thames, which in some visualisations gives the illusion that this is in fact two boroughs when it is not, so this needed to be kept in mind throughout analysis.

In terms of analysis python was used for all data manipulation and visualisation techniques. To determine any linear association between variables connected to mental health and the availability and proximity greenspace had, as well as testing linear associations with multiple other socio-demographic variables (e.g crime rate, average age, median income etc.) an Ordinary Least Squares (OLS) regression was used from the `spreg` package found in `PySAL`. Significant variables were determined from these regressions and successive analysis was then aimed at further research into these linear associations. The use of subplots to overlay visuals on each other were key components of visualisation in this work. This was made easy through use of the `matplotlib.pyplot` feature `subplots` which allows multiple plots to be drawn in one figure. As the data was all representative of the same study space, this was relatively straightforward.

Spatial autocorrelations were also done on the data. Spatial autocorrelation work under the basic principle of Tobler’s First Law (Tobler 1970): "everything is related to everything else, but near things are more related than distant things". Spatial autocorrelation analysis looks at the extent which values in an observed location are connected with values at neighbouring locations. The project used a metric of total house price divided by number of rooms called ‘Price per room’, and subsequent spatial autocorrelation tests were completed using ‘ESDA’ package in ‘PySAL’ on this value across the study space. Visualisation of spatial autocorrelation significance and direction was also obtained through a LISA map. The LISA map takes into account four concepts: the spatial distribution of raw local Moran's I values, pseudo p-values, quadrant locations, and final significant clusters.

Through use of the python package `contextily` it was possible to set visual analysis overlaid on a base map of London. For this method it was needed to set Coordinate Reference Systems (CRS) to be the same in order to overlay the maps with the same representation of the earth’s surface, without specifying the projections to be on the same CRS for one python won’t run the code, but more intuitively the projection of the world will be completely different and thus inaccurate.

It should be noted that while assessing greenspaces at a borough level and using house price data for analysis at a house by house level there does indeed persist the Modifiable Areal Unit Problem (MAUP), which for this instance means that when aggregating the house price points into their boroughs this does not take into account any cross-boundary usage of greenspaces and confines observations to the borough they are in which, in theory, may not be the case as people are free to roam to whichever greenspaces they may wish. Most likely, this effect would be most felt for those housing points on or close to borough boundaries. In order to minimise this on the spatial autocorrelation, K-Nearest-Neighbours were used on the housing price data which would not take into effect the borough boundaries, but rather make use of the boundary map afterwards for visual analysis.

**Results Greenspace effect on the socio-demographics in the boroughs**Greenspace percentages were plotted for the 33 boroughs of London (Fig. 1a); showing a large variance across the city. Percentages range from the ‘greenest’ borough, Havering (59.3% greenspace coverage) to the ‘least green’, City of London (4.8% coverage).

Map

Description automatically generated

a

Graphical user interface, application

Description automatically generated

b

Application

Description automatically generated with medium confidence

c

Fig. 1. a-c Greenspace percentages mapped for London (a) with the top five and bottom five boroughs in terms of greenspace coverage shown in (b) and (c) respectively

Results of the OLS regression model shown in Figure 2, revealed significant effects on depression rates per 1000 people at a significance level of 95% for greenspace, Crime Rate, Average age and Median income. The regression produced a high adjusted R2 value of 0.7782, informing that ~78% of the variation in depression episodes per 1000 people is caused by the variables included in this model. In terms of greenspaces effect on depression rates, the output tells us that for an increase in 1% of greenspace in a London borough, depression rates will drop by 0.137 per 1000 people for that borough. The model also informs that an increase in both crime rate and Median income would result in an increase in depression and that an increased average age in a borough would result in a decrease in depression.

Table

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Fig. 2. spreg OLS regression output showing significance for all the variables at a level of 0.05

Figure 3 and 4 below shows both greenspaces and average age plotted against depression rates by borough. Both plots visualise the positive impact that increasing both of these values would have on decreasing depression numbers with the impact of greenspaces seen to be noticeably strong, quickly reducing depression rates.

Chart, scatter chart

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Chart, scatter chart

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Fig. 4: the positive effect of increasing average age in London Boroughs on decreasing depression rates

Fig. 3: the striking effect of increased

Greenspace percentage on depression

rates

**Housing Price Analysis**

A Pearson’s correlation between average borough house price and greenspace abundance indicated a negative relationship between the two (-0.4297); that increasing greenspace is linked with decreasing average house price. This analysis whilst being informative at the borough level needed to be looked at with a more local view. In order to analyse this the housing price data was broken down to contain a representation of price per room. This value was initially tested for the presence of spatial autocorrelation, producing a large, significant Moran’s I value of ~0.709 and after repeated simulations to reference this Moran’s I value against, produced a significance value of 0.001 suggesting the observed value is statistically significant (Fig. 5). The Moran Local Scatterplot (Fig. 6) produces a visualisation of price per room vs lagged price per room and also of a measure of significance according to the set threshold of 0.05. The plot then colours significant data points based on the quadrant that they are located in, this will determine price per room "hotspots" (high-high), "coldspots" (low-low), "diamonds-in-the-rough" (high-low), or "doughnuts" (low-high).

Chart, line chart

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Chart, scatter chart

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Fig. 6: Moran’s Local Scatterplot showing price per room ‘hotspots’ (red), ‘coldspots’ (blue), ‘diamonds’ (yellow), ‘doughnuts’ (light-blue)

Fig. 5: Visualisation of the significance of the Moran’s I value observed (red)

In order to visualise the significant points from the Moran’s Local Scatterplot on the map of London, a LISA map was used (Figure 7). This produces a visualisation of the price-per-room data points on the map of London, indicating a cluster of significantly spatially autocorrelation of High-High (red) values in and around central London, thus, there are clusters of Higher price-per-room houses next to other higher price-per-room houses. The LISA map shows clusters around the outskirts of the London boroughs that possess Low-Low (blue) values. Interestingly these lower valued ‘rooms’ seem to be in the areas where there are the higher abundance of greenspaces.

Map

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Graphical user interface, application

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Fig. 7: The LISA map output showing large significant Low-Low values in 4 of the top 5 London Boroughs for greenspace abundance

**Map

Description automatically generated**Figure 8 below gives a representation of the LISA map findings for house prices in 2019. The points displayed in the figure are those houses that are greater than the overall house price mean for 2019. The sparsity in higher priced houses in the outskirts of the London boroughs, in the areas where greenspace abundance is at its highest points (yellow and light green shades of the map), is clearly evident. Intuitively there are clusters of higher priced houses in around the city centre, visualised both on the LISA map (red points) and below by the large gathering of points throughout the centre of the map. From this visualisation the spatial autocorrelation between the boroughs house prices is clearly evident.

Fig. 8: Housing points with a price greater than the mean, overlaid on the greenspace abundance map of London

**Discussion**

Studies regarding mental health have previously linked a positive impact of increased greenspace abundance on reducing depression numbers (Alcock et al 2013, Houlden et al 2019), the psychological idea behind this being that the lower abundance of stimuli allows for increased cognitive function and an opportunity for our brains to relax (Bratman et al. 2015). The findings in this study provide some evidence to support these claims, and thus back the EU and the UK governments’ guidelines for greenspace proximity to be within 300m of people’s homes. Whilst this proximity may not be possible to every dwelling, it provides a good benchmark recommendation that should be taken seriously. London presents itself as a good city for analysis on greenspace abundance as it is a city with ambitious plans to achieve with regards to improving greenspace coverage to 50% by 2050. This push for more greenery will provide excellent opportunities for comparative analysis as the greenspace percentage across the city increases.

Results of an OLS regression displayed a strong positive linear association between greenspace abundance and decreasing depression rates in London boroughs, this was also visually represented showing a striking decline in depression rates per 1000 people in ‘greener’ locations. The regression model also indicated that an increase in crime rates within London Boroughs presented a linear relationship with increasing depression rates, more research into these findings is needed to be done in order to determine which areas in London these associations presented themselves in, thus if crime rates are higher in the ‘poorer’ areas which studies show are typically more associated with higher depression rates (Remes et al 2019). The limitation here being that these statistics are calculated on the borough level, which examines large portions of London meaning that crime ‘hotspots’ and ‘coldspots’ may be occurring at smaller geographical areas but going unnoticed due to being averaged into the borough values.

Analysis of house price data indicated that across the study area there is significant amounts of spatial autocorrelation regarding a house price metric of ‘price-per-room’. Intuitively, the city centre of London was found to contain large clustering of High price-per-room areas surrounded by high-price-per-room areas. Interestingly the LISA map indicated significant Low-Low price-per-room clusters mainly in the boroughs containing the higher abundance of greenspaces.

Finally, visual analysis showed this spatial autocorrelation of the house price points to be viewed against the boroughs greenspace abundance, again the MAUP must be taken into account here as those living in houses positioned on or close to borough boundaries may make use of greenspace in neighbouring boroughs if they so please and ideally an intensive study of the greenspaces used by residents would be done to account for this.

**Conclusion**

Such that the evidence in this study point towards a strongly positive correlation between frequenting greenspaces and lowering depression rates, that even stronger recommendations towards making use of the vast amounts of greenery areas should be provided by local councils and governments. Recommendations should aim at promoting visits to greenspaces rather than just providing a distance measurement to them. In terms of other variables assessed towards affecting mental health, crime rate shows itself as the most ‘fixable’ issue. The model suggests that decreasing crime rates in boroughs would present a positive effect on depression rates, thus local councils and police efforts towards further minimizing crime by increased police patrol in crime hotspots, more CCTV, or greater expansion of neighbourhood watch programmes should be looked at.

More study evidently needs to be done into why increasing greenspace abundance seems to affect housing prices, while these areas are in the outskirts of London thus where housing prices are expected to be lower, a more localised examination into this negative influence may uncover other potential causes linked to this.

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